1. Introduction

Biological databases continue to grow rapidly. This development is reflected in increases in both the size and complexity of individual databases as good as in the proliferation of new databases. A huge body of data is thus available for the extraction of high level information, including the development of new concepts, concept interrelationships and interesting patterns hidden in the databases. Knowledge Discovery in Databases (KDD) is an emerging field combining techniques from databases, statistics, artificial intelligence which is concerned with the theoretical and practical issues of extracting high level information (or knowledge) from volumes of low level data.

The KDD is usually a *multi-phase* process involving numerous steps, like data preparation, preprocessing, search for hypothesis generation, pattern formation, knowledge evaluation, representation, refinement and management. Furthermore, the process may be repeated at different stages when a database is updated. The *multi-phase* process is an important methodology for the knowledge discovery from real-life data. Although the process-centric view has recently been widely accepted by researchers in the KDD community, few KDD systems provide capabilities that a more complete process should possess.

The KDD process is interactive in that human intervention might be required at any point. It is also iterative and can contain multiple loops between any two steps. At the core of KDD is data mining the application of specific tools for pattern discovery and extraction. The practical aspects of data mining include dealing with issues such as data storage and access, scalability of massive data sets, presentation of results and human machine interaction.

1.1 Electroencephalogram (EEG) Signal

Electroencephalography (*EEG*) (as shown in figure 1) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as

epileptic activity can create clear abnormalities on a standard EEG study. A secondary clinical use of EEG is in the diagnosis of coma, encephalopathies, and brain death. EEG used to be a first-line method for the diagnosis of tumors, stroke and other focal brain disorders, but this use has decreased with the advent of anatomical imaging techniques with high (<1 mm) spatial resolution such as MRI and CT. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution (not possible with CT or MRI) is required.

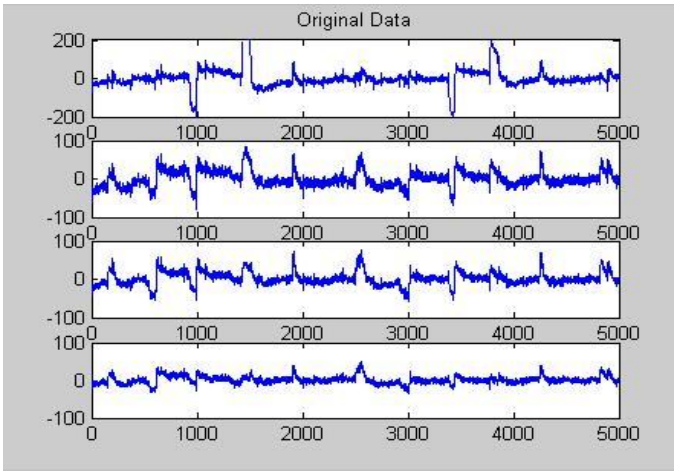

Figure 1 EEG Signal

Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psycho physiological research.

1.2 Sources of EEG Signal

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of similar charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbors, who push their neighbors, and so on, in a wave. This process is known as volume conduction.

When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG.

The electric potential generated by single neuron is far too small to be picked up by EEG or MEG. EEG activity therefore always reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signal because they are well-aligned and fire together. Because voltage fields fall off with the square of distance, activity from deep sources is more difficult to detect than currents near the skull.

Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning (e.g., waking and the various sleep stages). These oscillations represent synchronized activity over a network of neurons. The neuronal networks underlying some of these oscillations are understood (e.g., the thalamocortical resonance underlying sleep spindles), while many others are not (e.g., the system that generates the posterior basic rhythm). Research that measures both EEG and neuron spiking finds the relationship between the two is complex with the power of surface EEG in only two bands (gamma and delta) relating to neuron spike activity.

Below is a diagram (figure 2) of a neuron. It has several components: the soma is the cell body of the neuron and contains the nucleus, which houses genetic information; the dendrites extend from the soma and receive chemical messages from other neurons; the axon transmits electro-chemical signals to other neurons; the myelin sheath consists of fatty tissue cells that insulate the electrical current flowing through the axon; finally the bouton is responsible for converting an electrical signal to a chemical signal to be received by other neurons.

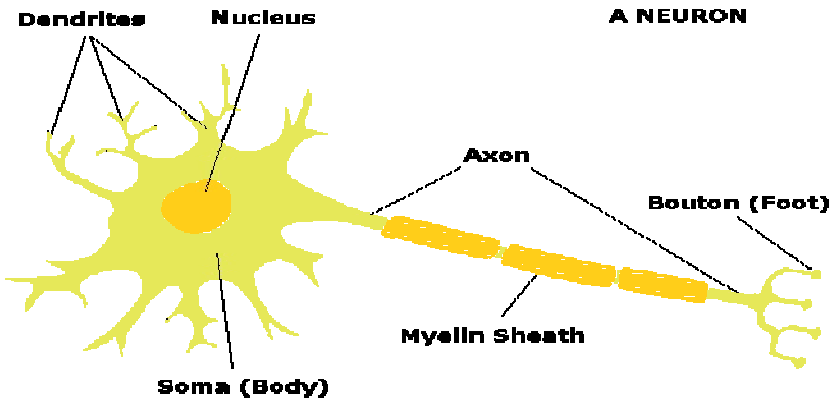

Figure 2 The Neuron: the most basic unit in the brain, and more generally, the nervous system

The processing of information takes place by the "firing" or pulsing of many individual neurons. The pulse is in the form of membrane depolarization traveling along the axons of neurons. A series of pulses in the neurons, also known as a spike train, can be considered the coded information processes of the neural network. The EEG is the electrical field potential that results from the spike train of many neurons. Thus, there is a relationship between the spike train and the EEG and the latter also encodes information processes of the neural-network

Measurement and analysis of the EEG can be traced back to Berger's experiments in 1929. Since then it has had wide medical applications, from studying sleep stages to diagnosing neurological irregularities and disorders. It was not until the 1970's that researchers considered using the EEG for communication. With the computer advances that ensued since then, active research in EEG utilization for communication has occurred in the last 10 years.

1.3 Research Use of EEG Signal

A routine clinical EEG recording typically lasts 20–30 minutes (plus preparation time) and usually involves recording from scalp electrodes. Routine EEG is typically used in the following clinical circumstances:

- ✓ to distinguish epileptic seizures from other types of spells, such as psychogenic non-epileptic seizures, syncope (fainting), sub-cortical movement disorders and migraine variants.

- ✓ to differentiate "organic" encephalopathy or delirium from primary psychiatric syndromes such as catatonia
- ✓ to serve as an adjunct test of brain death
- ✓ to prognosticate, in certain instances, in patients with coma
- ✓ to determine whether to wean anti-epileptic medications.

At times, a routine EEG is not sufficient, particularly when it is necessary to record a patient while he/she is having a seizure. In this case, the patient may be admitted to the hospital for days or even weeks, while EEG is constantly being recorded (along with time-synchronized video and audio recording). A recording of an actual seizure (i.e., an ictalrecording, rather than an inter-ictal recording of a possibly epileptic patient at some period between seizures) can give significantly better information about whether or not a spell is an epileptic seizure and the focus in the brain from which the seizure activity emanates.

Epilepsy monitoring is typically done:

- ✓ to distinguish epileptic seizures from other types of spells, such as psychogenic non-epileptic seizures, syncope (fainting), sub-cortical movement disorders and migraine variants.
- ✓ to characterize seizures for the purposes of treatment
- ✓ to localize the region of brain from which a seizure originates for work-up of possible seizure surgery.

Additionally, EEG may be used to monitor certain procedures:

- ✓ to monitor the depth of anesthesia as an indirect indicator of cerebral perfusion in carotid endarterectomy.
- ✓ to monitor amobarbital effect during the Wada test EEG can also be used in intensive care units for brain function monitoring:
- ✓ to monitor for non-convulsive seizures/non-convulsive status epilepticus
- ✓ to monitor the effect of sedative/anesthesia in patients in medically induced coma (for treatment of refractory seizures or increased intracranial pressure)
- ✓ to monitor for secondary brain damage in conditions such as subarachnoid hemorrhage (currently a research method)

If a patient with epilepsy is being considered for respective surgery, it is often necessary to localize the focus (source) of the epileptic brain activity with a resolution greater than what is provided by scalp EEG. This is because the cerebrospinal fluid, skull and scalp *smear* the electrical potentials recorded by scalp EEG. In these cases, neurosurgeons typically implant strips and grids of electrodes (or penetrating depth electrodes) under the dura mater, through either a craniotomy or a burr hole. The recording of these signals is referred to as electrocorticography (ECoG), subdural EEG (sdEEG) or intracranial EEG (icEEG)--all terms for the same thing. The signal recorded from ECoG is on a different scale of activity than the brain activity recorded from scalp EEG. Low voltage, high frequency components that cannot be seen easily (or at all) in scalp EEG can be seen clearly in ECoG. Further, smaller electrodes (which cover a smaller parcel of brain surface) allow even lower voltage, faster components of brain activity to be seen. Some clinical sites record from penetrating microelectrodes.

EEG, and the related study of ERPs are used extensively in neuroscience, cognitive science, cognitive psychology, and psycho physiological research. Many EEG techniques used in research are not standardized sufficiently for clinical use.

2. Motivations

There is a rapid grow in the volume of biological and clinical data or records. To exploit these data for discovering new knowledge that can be translated into clinical applications, there are fundamental data analysis difficulties that have to be overcome.

Many analytical tools based on machine learning approaches have been developed to handle such challenging data analysis problems. Around 1% of the total population in the world is affected by a neurological disease called epilepsy. A careful analysis of these EEG signals can solve many neurological disorder diseases.

3. Problem Statement

The whole problem of this research work can be categorized into two parts

- Extraction of features for analysis of EEG Signal
- Classification of EEG Signal

First of all a well defined process is required for feature extraction and analysis of a very transient signal (non-stationary) like EEG signal.

- Discrete Wavelet Transform

Secondly a well defined and well structured classifier model is required for classification of EEG signal to distinguish epileptic seizures from non-epileptic ones.

- Machine Learning Techniques

4. General and Specific Goals

The automatic classification of EEG patterns plays an important role in an EEG-based BCI system. It provides a new communication channel between human brain and computer. In neurology, the main diagnostic application of EEG is in the case of epilepsy as epileptic activity can create clear abnormalities on a standard EEG study. A secondary clinical use of EEG is in the diagnosis of coma, encephalopathy, and brain death etc. Epileptic seizures are caused by a disturbance in the electrical activity of the brain (and so they always start in the brain).

Around 1 in 5 people (20%) diagnosed with epilepsy who are then assessed at specialist epilepsy centers are found to have non-epileptic seizures (NES). Non-epileptic seizures (NES) are not caused by disrupted electrical activity in the brain and so are different from epilepsy.

5. Overall Framework of Research

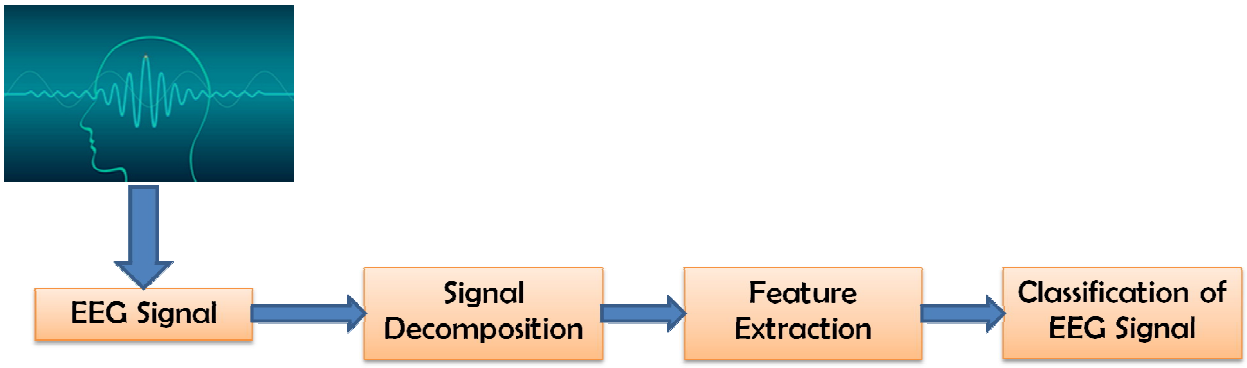

Figure 3 Model for EEG signal Analysis & Classification

6. Software used

- Matlab R2012a used for analysis and feature extraction of EEG brain signal using Discrete Wavelet Transform.
- Java 1.8 used for designing different classifier models with different training algorithms, kernel functions and basis functions.
- Eclipse Mars IDE used as an IDE for development
- Python 2.7.9 used for extracting features through different mathematical formulations.

7. Methodologies Adopted

The different methodologies adopted for this research work are as follows

- EEG dataset collection
- Analysis of EEG signal by decomposition
- Feature extraction & selection
- Classification of EEG signal for epilepsy identification
- Comparison of machine learning based classifiers
- Improvement over classifier performance through Swarm Intelligence based training algorithms

7.1 Analysis of EEG Signal and Feature Extraction

We need to construct a dataset (In feature – sample format) from EEG signal data. We need to analyze a very non-stationary or transient signal such as EEG to extract features from them. A publicly available EEG time series data has been used for this research. There are 5 sets like A, B, C, D and E, each containing 100 single channel EEG segments of 23.6 seconds each. Set A contains signals from subjects in a relaxed state with eyes open. Set B also contains signal same as A but ones with the eyes closed. The data sets C, D and E are recorded from epileptic subjects through intracranial electrodes for interictal and ictal epileptic activities. Set D contains segments recorded from within the epileptogenic zone during seizure free interval. Set C also contains segments recorded during a seizure free interval from the hippocampal formation of the opposite hemisphere of the brain. Set E only contains segments that are recorded during seizure activity.

The wavelet technique is a powerful tool for investigating small-scale oscillations of the brain signals. It provides an efficient way of representing signal on time frequency domain using the variable sized windows. The longtime windows are used for low-frequency resolution and short time windows for high-frequency. The wavelet transform decomposes the signal into different scales with different levels of resolution by dilating the mother wavelet

$$\emptyset_{a,b}(t) = \frac{1}{\sqrt{|a|}}\emptyset\left(\frac{t-a}{b}\right) \quad (1)$$

Where a is the scaling parameter and b is the shifting parameter. DWT uses multi-resolution filter banks and special wavelet filters for the analysis and reconstruction of signals. It includes iteration of filters with rescaling. The transform involves successive low pass and high pass filtering of the discrete time-domain signal. The resolution of the signal is determined by the filtering, and the scale is determined by up sampling and down sampling

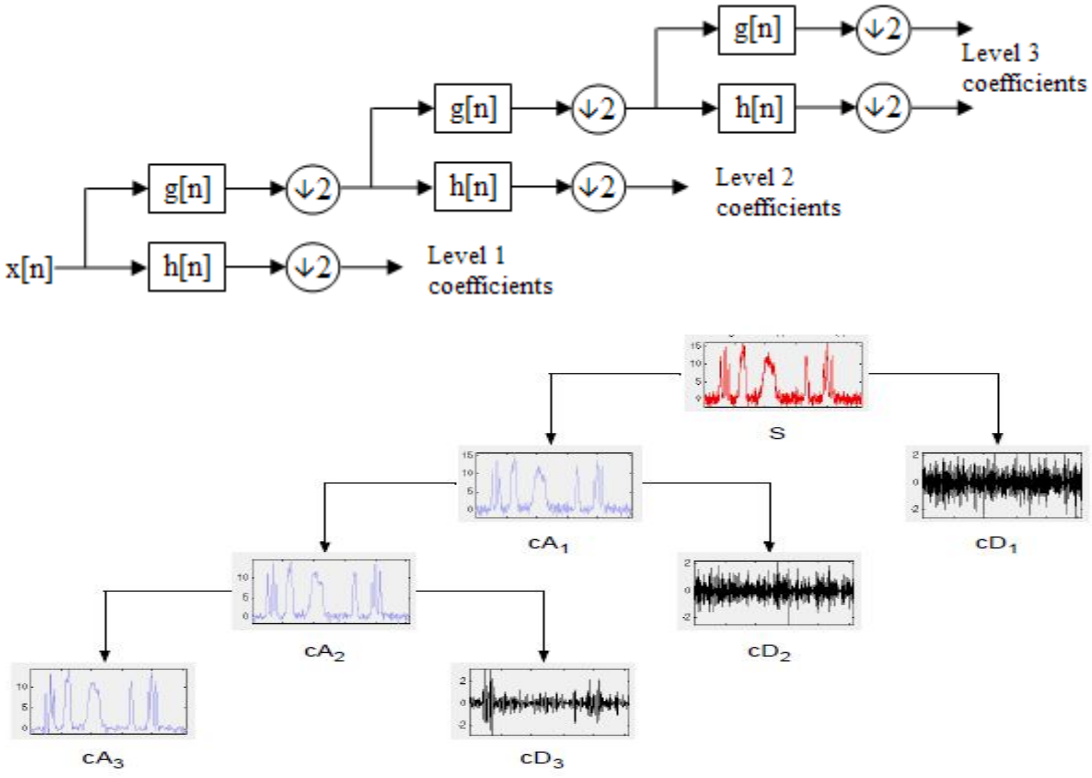

Figure 4 Signal Decomposition using DWT

One of the main advantages of wavelets is that they offer a simultaneous localization in time and frequency domain. The second main advantage of wavelets is that, using fast wavelet transform,

it is computationally very fast. Wavelets have the great advantage of being able to separate the fine details in a signal. Very small wavelets can be used to isolate very fine details in a signal, while very large wavelets can identify coarse details. In wavelet theory, it is often possible to obtain a good approximation of the given function by using only a few coefficients which is the great achievement in compare to Fourier transform. Wavelet theory is capable of revealing aspects of data that other signal analysis techniques miss the aspects like trends, breakdown points, and discontinuities in higher derivatives and self-similarity. The wavelet coefficients have been computed using Daubechies of order two and up to level four. This technique was found to be more suitable because of its smoothing features which are more appropriate to detect changes in EEG signal. For our work, the original signal have been decomposed as four detailed coefficients (d_1, d_2, d_3, d_4) and four approximation coefficients (a_1, a_2, a_3, a_4). For simplicity, all the approximation coefficients are ignored except the one in the last step i.e. a_4. Hence, the signal is decomposed into five segments by using DWT.

7.2Machine Learning based Classifier for Epileptic Seizure Identification

We need to study the performance of different machine learning based classifier to classify epileptic seizures and non-epileptic seizures. This study can reveal the architectural and functional benefits of different classifiers. After extracting the important features from EEG signal using above mentioned techniques, several methods can be used to design an efficient classifier which can classify epileptic and non-epileptic seizures. Machine learning techniques are the most efficient way of designing classifiers.

- Multilayer Perceptron Neural Network (MLPNN) : The different training algorithms used for MLPNN
  - ✓ Back-propagation - Activation Function – Sigmoid, Learning Rate = 0.7, Momentum Coefficient = 0.8, Input Bias – Yes.
  - ✓ Resilient-propagation - Activation Function – Sigmoid, Learning Rate = NA, Momentum, Coefficient = NA, Input Bias – Yes.
  - ✓ Manhattan update rule - Activation Function – Sigmoid, Learning Rate = 0.001, Momentum Coefficient = NA, Input Bias - Yes

Table 1: Experimental evaluation result of MLPNN with different training algorithms

Cases for Seizure Types	Multi-Layer Perceptron Neural Network with different Propagation Training Algorithms											
	Back-Propagation				Resilient-Propagation				Manhattan-Update Rule			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	100	90.09	94.5	16.52	99.009	100	99.5	2.846	97.29	77.77	85	7.541
Case2 (D,E)	100	83.33	90	22.22	99.009	100	99.5	2.547	55.68	78.78	60	7.181
Case3 (A+D,E)	100	86.95	92.5	23.12	95.85	85.98	92.33	14.79	93.78	82.24	89.66	14.85

- Support Vector Machines (SVM) : The different kernel functions used for SVM are
  - ✓ Linear Kernel - Kernel Type – Linear, Penalty Factor = 1.0
  - ✓ Polynomial Kernel - Kernel Type – Polynomial, Penalty Factor = 1.0
  - ✓ RBF Kernel - Kernel Type – Radial Basis Function, Penalty Factor = 1.0

Table 2: Experimental evaluation result of SVM with different kernel types

Cases for Seizure Types	Support Vector Machine with different Kernel Types											
	Linear				Polynomial				RBF			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	100	100	100	2.127	100	100	100	2.101	100	100	100	2.002
Case2 (D,E)	100	100	100	1.904	100	100	100	1.902	100	100	100	2.021
Case3 (A+D,E)	90.67	76.63	85.66	11.61	100	99.009	99.66	7.24	100	100	100	2.511

- Radial Basis Function Neural Network (RBFNN): Basis Function – Inverse Multiquadric, Center& Spread Selection – Random, Training Type– SVD (Singular Value Decomposition)
- Probabilistic Neural Network (PNN): Kernel Type – Gaussian, Sigma low – 0.0001 (Smoothing Parameter), Sigma high – 10.0 (Smoothing Parameter), Number of Sigma – 10.
- Recurrent Neural Network (RNN): Pattern Type – Elman, Primary Training Type – Resilient Propagation, Secondary Training Type – Simulated Annealing, Parameters for SA, Start Temperature – 10.0, Stop Temperature – 2.0, Number of Cycles - 100

Table 3: Experimental evaluation result of RBFNN, RNN, PNN with different training algorithms

sCases for Seizure Types	Other Types of Neural Network											
	RBF Neural Network				Probabilistic Neural Network				Recurrent Neural Network			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	83.076	65.925	71.5	2.051	100	100	100	0.967	77.173	73.148	75	10.31
Case2 (D,E)	100	97.08	98.5	1.828	100	100	100	0.977	64.705	71.604	67.5	13.29
Case3 (A+D,E)	92.30	66.41	81	2.928	100	100	100	1.616	67.346	66.666	67.333	19.58

7.3 Accuracy Improvement of RBFNN using Modified PSO Training Algorithm

Due to the architectural simplicity and high approximation capability of RBFNN we can take it as a challenge to improve the performance of this technique. We need to improve the performance of RBFNN by utilizing the efficiency of swarm based optimization technique such as Particle Swarm Optimization. This algorithm is a nature inspired algorithm that is inspired from the behavior of bird flocks called as swarm. The main computational steps of PSO includes generating initial position & velocity of each particle in population, updating position and velocity for a certain number of generations to get the optimal solution. One of the important drawbacks of PSO algorithm is its very slow searching around the global optimum. Hence an improved PSO algorithm has been proposed to do a faster search around the global optimum.

In velocity update formula the inertia weight (λ) is generally taken as a constant value for the total number of generations. This can be modified by decreasing λ gradually as the number of generations (or iteration) increases. Thus we can reduce the search space for global optimum by reducing the value as the number of generation increases. After each generation the best particle in the previous generation will replace the worst particle in current generation. In this research work we have applied two types of selection strategy sequentially for inertia weight, linear and non-linear selection. In linear selection λ should reduce rapidly, while around the optimum λ will reduce slowly.

Mathematically, Let λ_0 is the initial value of inertia weight, λ_1 is the end point of linear selection, g_1 is the number of generations for linear selection and g_2 is the number of generations for non-linear selection.

$\lambda_1=\lambda_0 - \big((\lambda_1/g\,1) * i\big)$, where i=1,2,3,...,g1 (2)

$\lambda_1 = (\lambda_0 - \lambda_1) * \exp\big(((g1 + 1) - i)/i\big)$, where i=g1...$g2$ (3)

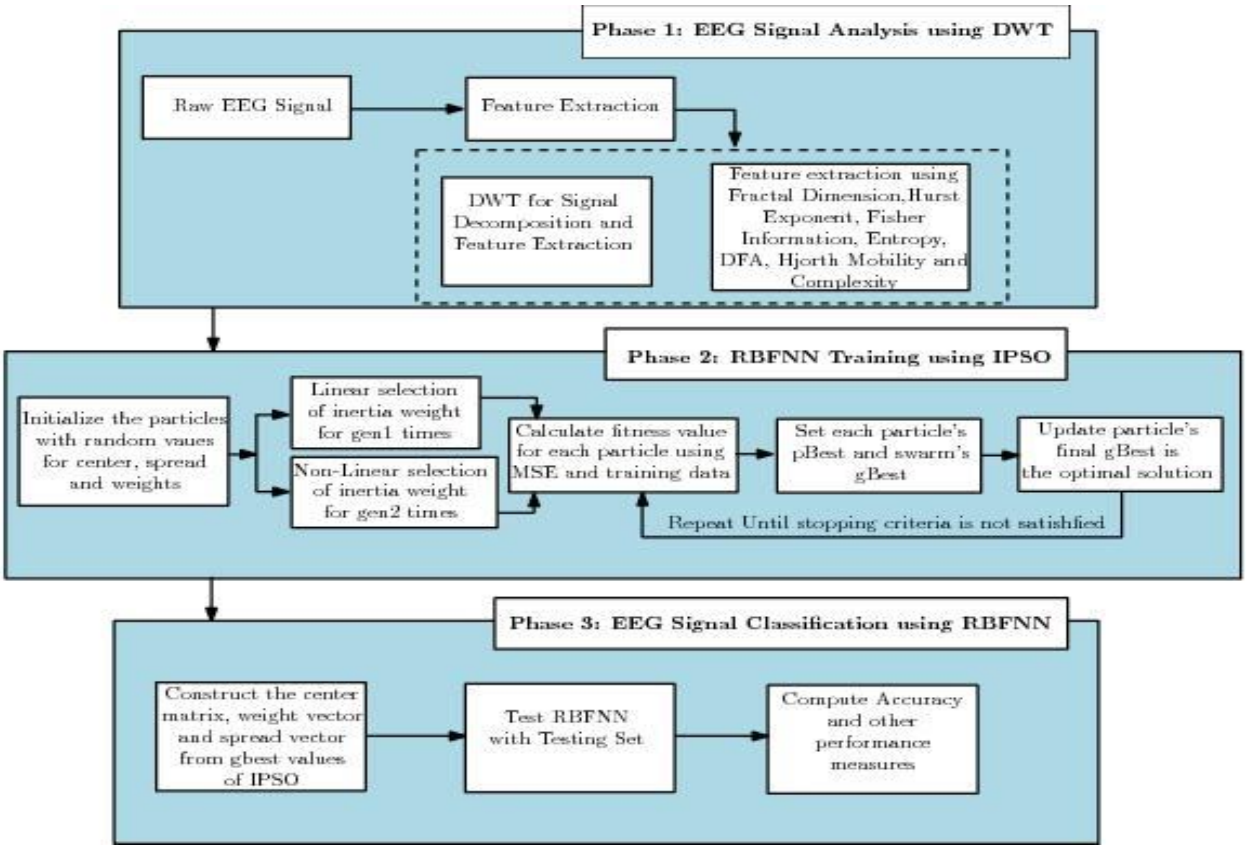
Phase 1: EEG Signal Analysis using DWT
Raw EEG Signal
Feature Extraction
DWT for Signal Decomposition and Feature Extraction
Feature extraction using Fractal Dimension, Hurst Exponent, Fisher Information, Entropy, DFA, Hjorth Mobility and Complexity
Phase 2: RBFNN Training using IPSO
Initialize the particles with random vaues for center, spread and weights
Linear selection of inertia weight for gen1 times
Non-Linear selection of inertia weight for gen2 times
Calculate fitness value for each particle using MSE and training data
Set each particle's pBest and swarm's gBest
Update particle's final gBest is the optimal solution
Repeat Until stopping criteria is not satishfied
Phase 3: EEG Signal Classification using RBFNN
Construct the center matrix, weight vector and spread vector from gbest values of IPSO
Test RBFNN with Testing Set
Compute Accuracy and other performance measures

Figure 5 Proposed model for classification of EEG signal using modified PSO algorithm

Table 4: Training and Testing Accuracy Comparison of RBF Network (Inverse Multi-quadric) trained with GD, PSO and IPSO (Confidence level 95%)

Datasets used in Experiment	RBF Trained with GD		RBF Trained with General PSO		RBF Trained with Improved PSO	
	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy
EEG for Epilepsy (Set A & E)	97.0 ± 0.033	70.0 ± 0.089	97.0 ± 0.033	96.00 ± 0.038	99.0 ± 0.019	99.0 ± 0.019
EEG for Epilepsy (Set D & E)	89.2±0.060	84.0 ± 0.071	98.0±0.027	96.00 ± 0.038	99.0±0.019	97.0 ± 0.033
EEG for Epilepsy (Set A+D & E)	80.4±0.063	75.3 ± 0.069	85.7±0.056	78.6 ± 0.065	90.6±0.046	84.6 ± 0.057

Table 5: Comparison of performance of RBF Network (Gaussian) trained with GD, PSO and IPSO (Confidence level 98%)

Datasets used in Experiment	RBF Trained with GD		RBF Trained with General PSO		RBF Trained with Improved PSO	
	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy
EEG for Epilepsy (Set A & E)	97.0 ± 0.039	70.0 ± 0.106	97.0 ± 0.039	96.00 ± 0.0456	99.0 ± 0.023	99.0 ± 0.023
EEG for Epilepsy (Set D & E)	89.2±0.072	84.0 ± 0.085	98.0±0.032	96.00 ± 0.0456	99.0±0.023	97.0 ± 0.039
EEG for Epilepsy (Set A+D & E)	80.4±0.075	75.3 ± 0.100	85.7±0.066	78.6 ± 0.095	90.6±0.055	84.6 ± 0.084

7.4 Accuracy Improvement of RBFNN using Modified ABC Training Algorithm

Due to the architectural simplicity and high approximation capabilities of RBFNN we can take it as a challenge to improve the performance of this technique. We need to improve the performance of RBFNN by integrating Artificial Bee Colony algorithm as a training algorithm.

RWS is difficult to solve real world problems as it is suitable for only maximization problems. Fitness values have to be converted for solving minimization problems. RWS has no parameter to control selection pressure. Tournament selection preserves diversity, as it gives chance to all individuals to be selected.

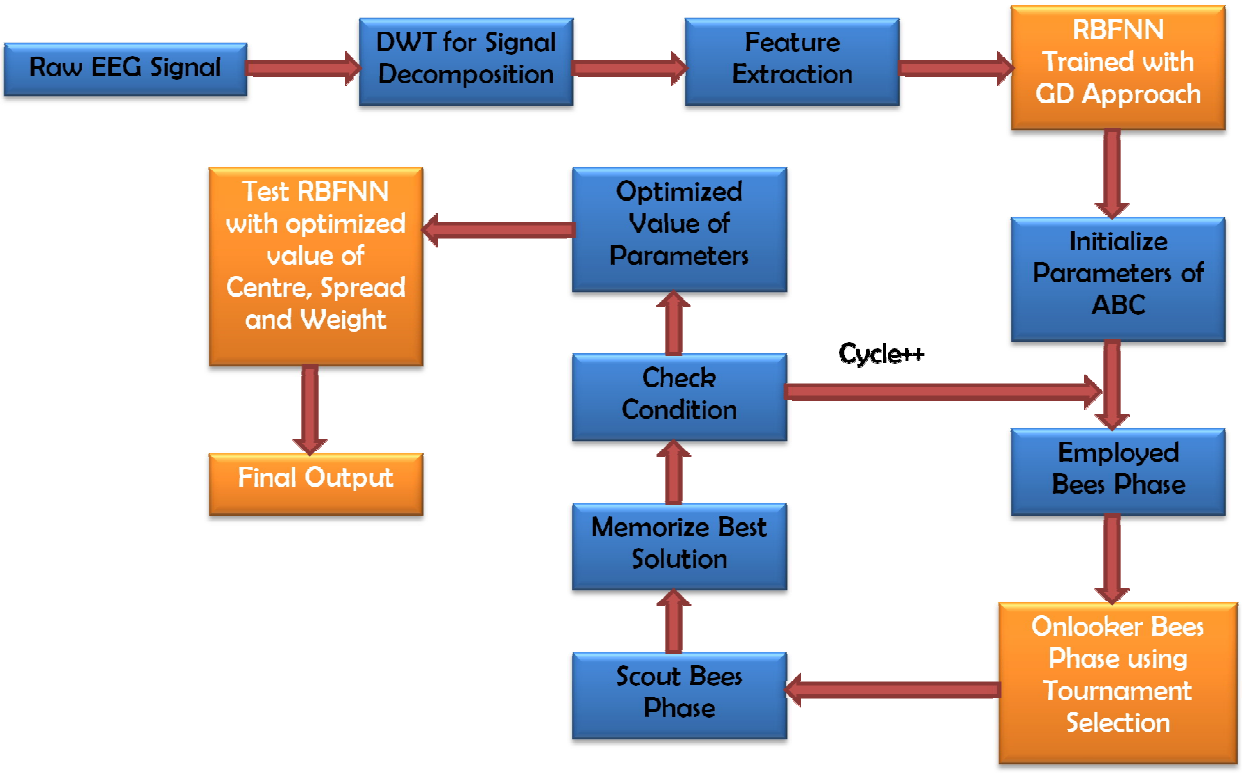

Figure 6 Proposed model for EEG signal classification using modified ABC algorithm

Table 6: Performance Comparison between GD learning and ABC learning with Inverse-multi-quadric RBFN

Experiments	Specificity		Sensitivity		Accuracy	
	RBFNN with GD	RBFNN with ABC	RBFNN with GD	RBFNN with ABC	RBFNN with GD	RBFNN with ABC
Set A & E	84.1	85.7	65.7	66.4	71.5	72.5
Set D & E	100.0	100.0	80.0	88.5	87.5	93.5
Set A+D & E	76.8	95.6	63.2	66.0	73.3	81.6

Table 7: Performance Comparison between ABC learning and Modified ABC learning with Inverse-multi-quadric RBFN

Experiments	Specificity		Sensitivity		Accuracy	
	RBFNN with ABC	RBFNN with MABC	RBFNN with ABC	RBFNN with MABC	RBFNN with ABC	RBFNN with MABC
Set A & E	85.7	88.1	66.4	66.0	72.5	73.5
Set D & E	100.0	100.0	88.5	97.0	93.5	98.5
Set A+D & E	95.6	96.0	66.0	68.4	81.6	83.0

8. Conclusion

We have performed a very detailed analysis to extract features from EEG brain signal using DWT and other techniques. We have performed an empirical study on different machine learning based classification techniques to classify epileptic and non-epileptic seizures. We have modified the basic PSO algorithm to optimize parameters of RBFNN to improve its performance. We have also modified the basic ABC algorithm to optimize parameters of RBFNN to improve its performance and compared the results with previous technique.

9. Constraints

One of the main constraints in this research work is the collection of real time data, as it requires a deep knowledge of decoding the numerical values from the machine that records EEG.

10. Dissemination of Work

[1] Sandeep K. Satapathy, Satchidananda Dehuri, Alok K. Jagadev, ABC Optmized RBF Network for Classification of EEG Signal for Epileptic Seizure Identification, *Egyptian Informatics Journal*, 2016 . **(Elsevier Publication) (Article In Press)**

[2] Sandeep K. Satapathy, Satchidananda Dehuri, Alok K. Jagadev, A comparative Analysis of Feature Extraction and Machine Learning based Classifier for EEG Signal Classification, *International Journal of Pharma and Bioscience*, 7(3), pp. 895-906, 2016.

[3] Sandeep K. Satapathy, Satchidananda Dehuri, Alok K. Jagadev, An Empirical Analysis of Different Machine Learning Techniques for Classification of EEG Signal to Detect Epileptic Seizure, *International Journal of Applied Engineering Research*, 11(1), pp 120-129, 2016.

[4] Sandeep K. Satapathy, Alok K. Jagadev, Satchidananda Dehuri, An Empirical Analysis of Training Algorithms of Neural Networks: A Case Study of EEG Signal Classification Using Java Framework, *In L. C. Jain, et al. (Eds.), Advances in Intelligent Systems and Computing, Springer*, 309, pp. 151-160, 2015.

[5] Sandeep K. Satapathy, Alok K. Jagadev, Shruti Mishra, Satchidananda Dehuri, Sung-Bae Cho, A Bird's-Eye View on Feature Extraction in EEG Brain Signal Analysis and Performance Comparison of Classifiers, *In Proceedings of International Conference on Control, Computing, Communication and Materials* (ICCCCM), 2013, IEEE.

[6] Sandeep K. Satapathy, Satchidananda Dehuri, Alok K. Jagadev, EEG Signal Classification using RBF Network Trained with Improved PSO algorithm for Epilepsy Identification, *Informatics in Medicines Unlocked*. **(Under 2nd Review) (Elsevier Publication)**

References

1. Niedermeyer, E. and Lopesda Silva, F. 2005. Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. 5th edition Lippincott Williams and Wilkins, London.
2. Finley, K.H., Dynes, J.B. 1942. Electroencephalographic studies in epilepsy: a critical analysis, Brain, 65, pp. 256–265.
3. Sanei, S. and Chambers, J.A. 2007. EEG Signal Processing. Wiley, NewYork.
4. Lehnertz, K. 1999. Non-linear time series analysis of intracranial EEG recordings in patients with epilepsy--an overview. International Journal of Psychophysiology, 34(1), pp.45-52.
5. Alicata, F.M., Stefanini, C., Elia, M.. Ferri, R., Del Gracco, S. and Musumeci, S.A. 1996. Chaotic behavior of EEG slow-wave activity during sleep. Electroencephalography and Clinical Neurophysiology, 99(6), pp. 539–543.
6. Ocak, H. 2009. Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. Expert Systems with Applications, 36(2), pp. 2027–2036.
7. Acharya, U.R., Sree, S.V. , Swapna, G., Joy Martis, R., and Suri, J.S. 2013. Automated EEG analysis of epilepsy: A review", Knowledge Based System, 45, pp. 147-165.
8. Fathi, V., Montazer, G. A. 2013. An improvement in RBF learning algorithm based on PSO for real time applications, Neurocomputing 111. 169–176
9. Mazurowski, M.A., Habas, P.A., Zurada, J.M., Lo, J.Y., Baker, J.A., Tourassi, G.D., 2008. Training neural network classifiers for medical decision making: the effects of imbalanced datasets on classification performance. Neural Networks 21 (2–3), 427–436.
10. Zhang, J., Lok, T., Lyu, M., 2007. A hybrid particle swarm optimization-back-propagation algorithm for feedforward neural network training. Applied Mathematics and Computation 185 (2), 1026–1037.
11. Ge, H.W., Qian, F., Liang, Y.C., Du, W.L., Wang, L., 2008. Identification and control of nonlinear systems by a dissimilation particle swarm optimization-based elman neural network. Nonlinear Analysis: Real World Applications 9 (4), 1345–1360.
12. Zhao, L., Yang, Y., 2009. Pso-based single multiplicative neuron model for time series prediction. Expert System Application 36, 2805–2812.
13. Guerra, F.A., Coelho, L.D.S., 2008. Multi-step ahead nonlinear identification of lorenz's chaotic system using radial basis neural network with learning by clustering and particle swarm optimization. Chaos. Solitons & Fractals 35 (5), 967–979.